Partisan Bias in Professional Macroeconomic Forecasts*

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Abstract

Combining forecasts from the Wall Street Journal's Economic Forecasting Survey with voter registration and political contribution data, we investigate the role of partisan bias in professional forecasting. We document that macroeconomic expectations of professional forecasters are systematically related to their affiliation with the political party in control. Democrat-affiliated forecasters have GDP growth forecasts that are 0.4 percentage points higher than Republicans when the Democrats control the White House (relative to when Republicans control it). There is suggestive evidence that changes in control of the House and the Senate also affect professional forecasts in a manner like control of the executive office. We discuss the implications of our results for the large literature that uses professional forecasts to study the role of deviations of expectations from the commonly used friction-less rational expectations benchmark.

JEL codes: C53, D72, E37, E65

*Preliminary and incomplete. Please do not circulate. We are grateful to the Wall Street Journal for making their survey data available to researchers. Emails: benjamin.s.kay@frb.gov, jryngaer@nd.edu, lakdawa@wfu.edu, and michael.futch@civitech.io.

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1 Introduction

Recently, interest has increased in departures of economic expectations from the benchmark full-information rational expectations framework (FIRE) that has been pervasive in macroeconomics for many decades. Political polarization presents one intriguing departure from this benchmark. Specifically, expectations appear to be strongly affected by the agents' affiliation with the political party that is in control. A large and growing strand of the literature has primarily focused on household expectations and found strong evidence for partisanship, for recent examples see Mian et al. [2021] and Binder [2023]. In this paper we investigate whether the political affiliation of professional forecasters is systematically related to their macroeconomic forecasts. Professional forecasters–whose job it is purportedly to objectively forecast macroeconomic outcomes using all available information–are probably the closest real-world equivalents to the FIRE agents in economists' models. Our paper documents that, even for professional forecasters, there is substantial evidence that political affiliations affect their economic expectations.

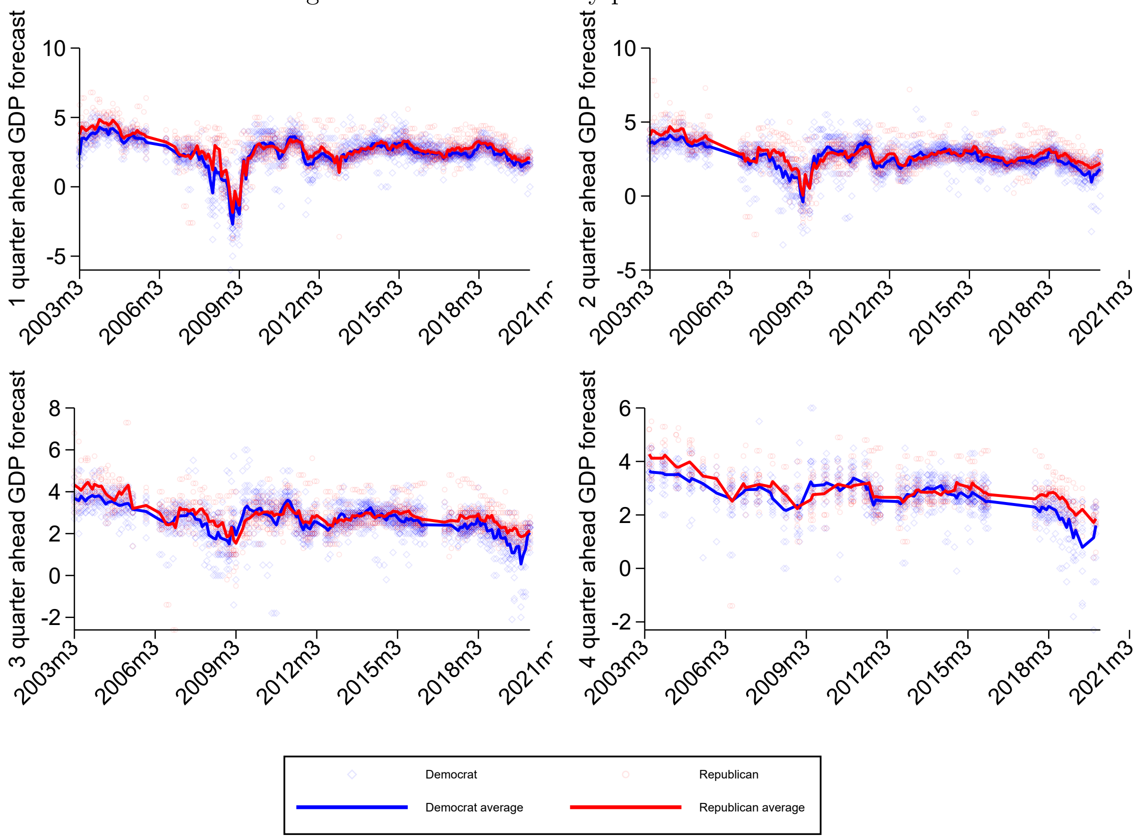
We use the survey of macroeconomic forecasts collected by the Wall Street Journal and made available publicly on their website. The data are available at wsj.com. This is a monthly survey with data available from 2003 to 2020 that asks the respondents about their forecasts for various macroeconomic indicators and financial market variables. For our purposes the key feature of this survey is that the name of individual forecasters is also made publicly available (that is, the survey is eponymous). This contrasts with other commonly used surveys like the Survey of Professional Forecasters where the forecasts are anonymized. We use these names to match the individual forecasters with their political affiliation.

To match the political affiliation of forecasters we use two main sources. First, we attempt to match political affiliation from publicly available voter registration records. In gathering the voter registration records we use data from Civitech and Lexis Nexis database. [some details here]. A caveat to this approach is that we only observe each forecaster's most recent political registration. This means that we may be partly mischaracterizing a forecaster's affiliation if they have changed political affiliation in our sample. Second, we use data on political contributions made publicly available by the Federal Election Commission.[1] We have 147 unique forecasters in our WSJ survey response sample. From the 147, we can match about 76 to a clear partisan affiliation, and most of our analysis will only focus on this sub-population.

To characterize which political party is in control we use two main approaches. First, we simply use the political party of the president to characterize each month in our sample as being under Democratic

[1] Available at the FEC's website: https://www.fec.gov/introduction-campaign-finance/how-to-research-public-records/individual-contributions/.

Figure 1: GDP forecasts by political affiliation



Source: The Wall Street Journal, FEC, Civtech, and author's calculations.

or Republican control. Of course, there are varying levels of control that two political parties have in enacting legislation and implementing policy based on the control of (and share of seats in) the House and the Senate. To capture this, we use the measure of political control developed by Roper [citation here]. The first measure assigns a simple weight to whether the political party controls the House, Senate and the Presidency, this measure goes from 0 to 7 with 0 being complete Republican control and 7 being complete Democratic control. The second measure uses the share of seats in the Senate and House to create a more granular measure that varies from 0 to 2, again with 0 being full Republican control and 2 being full Democratic control.

Our main result is that forecasters' GDP forecasts are materially affected by the alignment of their political affiliation with the political party in power. This result can even be gleaned from just plotting the raw data. Figure 1 plots the GDP forecasts for all the forecasters with matched affiliation, with Democrat forecasts shown in blue triangles and Republican forecasts shown in red circles. The figure also shows the mean across Democrat and Republican forecasters for each month in blue and red lines respectively. The four subplots in the figure are for GDP forecasts for 1-,2-,3- and 4-quarter ahead forecasts. Finally, the shaded background shows the three presidential regimes of George W. Bush, Barack Obama, and Donald Trump.

In the Bush presidency from 2003 to 2008, democratic forecasts are systematically lower than Republican forecasts with the blue line (average) consistently below the red line. This pattern is more easily discernible for the longer horizon forecasts. In the Obama presidency there appears to be no systematic difference with the blue line sometimes above and sometimes below the red line. However, with the Trump presidency beginning in 2017 we see a clear divergence with Democratic forecasts moving considerably lower than Republican forecasts. Of course, this is just eye-ball econometrics, and we now proceed to test the difference more formally between the forecasts and their relationship between the forecaster political affiliation and the political party control. In addition to using the party of the president to indicate political control, we will also use the Roper measure discussed above which captures changes in share of the Senate and the House controlled by the political parties.

We confirm this result with formal econometric techniques and show that the effect of partisan affiliation on macroeconomic forecasts is strongly statistically significant. Specifically, we use a difference-in-differences approach to compare the difference between Democratic and Republican forecasters in periods with a Democratic president relative to periods with a Republican president. Because our "treatment" (i.e., the change in the president) applies uniformly to all forecasters, our framework is immune from the recent concern about using the difference-in-differences framework with staggered treatment, see for example Baker et al. [2022]. Focusing on two-quarter ahead GDP forecasts we find that Democratic-affiliated forecasters have a forecast that is 0.4 percentage points higher than Republican-affiliated forecasters when the president is a Democrat (relative to when the president is a Republican).

In our sample we have three presidents (George W. Bush, Barack Obama and Donald Trump). We find that our results are essentially driven by the difference in forecasts arising under the Republican presidents. In the Obama presidency, the GDP forecasts of forecasters affiliated with Republicans or Democrats are very similar to each other. The difference is both economically and statistically insignificant. However, under Republican presidents, Democrats are considerably less optimistic about GDP growth relative to Republicans. Our average difference-in-differences estimate of 0.4 percentage points is almost completely driven by the tenure of the Republican presidents.

While the presidential election is every four years, there are mid-term elections every two years and special elections that can sway the control of the House and/or the Senate. To capture changes in political control that can potentially happen at a higher frequency than the presidential cycle we use David Roper's Democrat Control Index [Roper, 2002]. This index creates a composite score of political control based on weighing control of the Senate, House and presidency. Using this measure, we find results consistent with results using the president of the party as the measure of political control. The difference between Democratic and Republican affiliated forecasts of GDP is negative when the Roper index is low (indicating higher control by the Republican party) and is positive when the Roper index is high (indicating higher control by the Democratic party).

This suggests that changes in the control of the House and the Senate also appear to be related to the partisan tilt of macroeconomic forecasters. However, we emphasize a caveat in the interpretation of these results based on the following observations. In our sample the two big changes in the Roper Index (2016 and 2008) also coincide with a change in the presidency after two terms of the opposition party president. Motivated by this, we conduct two specific event-studies where we zoom in on the months around these two presidential elections. Using an event-study framework we show that for both these cases, the election of the new president substantially increased the gap in forecasts between Democrats and Republicans consistent with our main result. In other words, after the Obama election Democratic forecasts got more optimistic relative to Republican ones. And after the Trump election Republican forecasts got relatively more optimistic.

The rest of the paper is organized as follows. The next section conducts a detailed literature review which is followed by a discussion of the different data sources we use to match the forecasters in the Wall Street Journal survey with their political affiliation. Section 4 discusses our main results and is followed by concluding remarks.

2 Literature Review

Our paper fits into four different strands of the literature. First, papers making use of the Wall Street Journal (WSJ) forecast data. Second, the role of politics and partisanship in economic forecasting. Third, biases in forecasting. Fourth, the cognitive consequences of politics and partisanship.

2.1 Research Using the WSJ

Our paper uses survey data from the WSJ (described in greater detail in Section 3). Survey respondents are mostly a mix of academic, business, and financial economists, who provide forecasts for prestige and (both personal and employer) marketing reasons. These motives may incentivize sub-optimal forecasts, a topic we will return to later. Despite the orientation of the WSJ survey to the needs of the newsroom and their news reading audience, there is a long tradition (if modest in aggregate volume) of using the survey for academic research.

To our knowledge, the first was Belongia [1987], who used the survey to compare professional forecasts of interest rates with market forecasts implied by futures prices. Another early paper is McNees [1992], who used the survey through 1991 to measure the size of economic forecast errors.

Schuh et al. [2001] extends the analysis of McNees [1992] to include the surveys through 2000. Kolb and Stekler [1996a] also looks at individual forecaster performance in the WSJ data, assessing individual forecaster accuracy, the value of these forecasts, and compares individual forecasts with the cross-forecaster consensus.

Of particular interest is Cho and Hersch [1998], which is an early forecasting paper using the WSJ data and biographical data. They also exploit the survey's eponymity, in there case to link respondent names to professional and educational experience: years of professional experience (29 years on average!), working in the federal reserve system, possessing a PhD (about 75%), and employer type (about 75% investment or commercial banks). Since our work looks for disagreement by economists when they are divided by partisan affiliations, it is also connected to papers looking for the existence of a consensus forecast. Kolb and Stekler [1996b] documents with the WSJ survey data that a forecast consensus only exists in about half of the surveys. This leaves substantial opportunity for disagreement.[2]

Greer [2003] uses the WSJ survey to test the directional accuracy of long term forecasts. Eisenbeis et al. [2002] also uses the WSJ to evaluate forecast accuracy, with an innovation that lets them simultaneously consider forecast accuracy across many different forecast types and without a balanced forecast panel. Dreger and Stadtmann [2008] uses the WSJ to explore how forecaster level beliefs on the path of macroeconomic conditions affects expectations of the USD/JPY exchange rate.

2.2 Research on Politics in Forecasting

Politicians, political parties, voters, and their agents may prefer less accurate economic forecasts (at least in public) as a tool for accruing and retaining political power and winning on matters of public policy. Ericsson [2017a] finds that political concerns encourage the IMF to make overly optimistic forecasts. Similarly, Dreher et al. [2008] finds that the IMF makes optimistic (biased) forecasts of growth and inflation when their domestic elections are approaching. IMF forecasts are also optimistic when the country has large IMF loans outstanding. This suggests a mechanism, outside of irrationality, for partisanship to affect forecasts in the WSJ survey. Economists are people, people are partisan, partisans want their side to win elections, and perceptions of the health of the economy shape incumbent electoral success. In the United States, government agencies regularly forecast the national debt a year hence. While we might expect the executive branch to make an overly optimistic (too low) debt forecast to exaggerate the health of the economy and minimize the costs of new programs. That said, Cassidy et al. [1989] finds that US state government revenue forecasts are very mildly biased (about 0.5 percent below actual) and finds that this bias is not systematically related to state political and institutional factors. Similarly, Ericsson [2017b] finds no evidence that political concerns bias federal

[2] An aggregate consensus is possible even if group forecasts are different, as long as the difference between groups is small relative to the difference within groups.

debt forecasts.

However, this is not a robust finding. Boylan [2008] detects substantial bias in state government spending forecasts in the periods right around elections (when the returns to a rosy forecast may exceed the costs of an inaccurate one). Ericsson [2017b] finds that OMB (government) forecasts of federal spending are consistently biased to be less than actual spending. Corder [2005] finds that while US government agencies make unbiased short term forecasts of economic performance, their long term forecasts are severely biased. Kamlet et al. [1987] also finds that executive branch and CBO forecasts are consistently biased to be optimistic. Outside the US, Frankel and Schreger [2013] finds that European government forecasts are biased in the optimistic direction, and especially so when the budget deficit is near the Stability and Growth Pact "ceiling" of three percent of GDP. Not all forecasters suffer equally from these political influences. Frankel and Schreger [2016] finds these optimistic forecasts are more common in the public sector: government forecasts of GDP growth and deficit spending are typically more over-optimistic than private sector forecasts.

2.3 Research on Statistical Biases in Forecasting

This paper explores partisan bias in forecasting, in both the sociological and statistical sense of the word. Sociologically, because partisanship is, in part, a form of unreasoned judgment. Statistically, because partisanship, we will show, also causes systematic deviations from the true value in economic forecasts. This subsection discusses the literature on statistical bias in economic forecasts.

Zarnowitz [1985] finds bias and serially correlated errors in quarterly forecasts of real GNP growth, inflation, unemployment, and other variables. Inflation has the most common systematic errors. Composite group forecasts generally have less bias and correlated errors than individual forecasts. Keane and Runkle [1990] revisits the data used in Zarnowitz [1985] with new statistical methods and finds strong evidence that price forecasts are rational.

Several studies have found that are biased because of forecaster irrationality. Ehrbeck and Waldmann [1996] finds that behavioral, rather than rational reasons explains the patterns of forecaster bias. Batchelor [2007] finds irrational bias in the persistent optimism (and the persistent pessimism of others) found in the real GDP and inflation forecasts of private sector forecasters in the G7 economies in the years 1990–2005. Capistrán and Timmermann [2009] observes that disagreement in inflation survey forecasts varies systematically with the level and variance of current inflation. They find that asymmetries in the forecasters' costs of over- and under-predicting inflation can explain this phenomenon. This paper adds to this literature by showing that partisanship, is an additional source of statistical bias that degrades forecast quality.

In contrast, Laster et al. [1999] finds theoretical and empirical evidence that some forecasting bias is rational. Specifically, forecasters whose wages depend most on publicity produce forecasts that differ most from the consensus. Similarly, Elliott et al. [2008] notes that while empirical work using survey forecast data frequently identifies forecaster bias and irrationality, they find that existing rationality tests are not robust to even small deviations from symmetric loss and hence have little ability to tell whether the forecaster is irrational, or the loss function is asymmetric. Empirical applications of their methodology suggests that rejections of rationality may have been driven by the assumption of squared loss.

2.4 Research on Cognitive Consequences of Politics

Exactly because partisanship is partly a form of unreasoned judgment, it can cause people to make inferior decisions. An early paper in the role of partisanship in creating bias is Abramowitz et al. [1975]. They submitted similar papers to social psychology journals on the differences between political activists' and nonactivists' psychological well-being. The submissions were identical, except that all references to activists and to nonactivists in the results and discussion were interchanged. They found that reviewer publication verdicts were biased by a reviewer's political orientation. This is particularly problematic in social psychology which has lost nearly all its political diversity over the last 50 years (Duarte et al. [2015]).

My-side bias is the tendency to generate and evaluate evidence in a manner biased toward the evaluator's opinions. It is closely related to motivated reasoning, the tendency to base conclusions on personal goals and emotions rather than on objective evidence. Bénabou [2015] provides a review of the extensive and growing literature on the role of motivated beliefs in economic phenomena. Kahan et al. [2017] presents experimental evidence that cultural conflict is disabling the faculties that members of the public use to make sense of decision-relevant science. Subjects' responses became politically polarized – and even less accurate – when the same data were presented as results from the study of a gun control ban instead of a skin rash treatment. Surprisingly, and particularly relevant for our analysis, subjects highest in numeracy, did substantially better than average on the apolitical experiments but worsened the effects of partisanship in political one.

Pennycook and Rand [2019] challenges the motivated reasoning explanation, saying that it is more accurately described as laziness. They find a measure of analytical reasoning, is negatively correlated with the perceived accuracy of fake news, and positively correlated with the ability to discern fake news from real news – even for headlines that align with individuals' political ideology. They suggest that solutions to fake news processing problems are better fought with interventions that are directed at making the public more thoughtful consumers of news media instead of making people less ideological.

Ironically, the cognitive consequences of partisanship are bipartisan. Ditto et al. [2019] provides a meta-analysis of 51 studies experimental studies of Republican partisan bias. Contrary to some individual studies, they find that Liberals and conservatives (showed no difference in mean levels of bias across studies.

We hope that careful thinking and deliberation, what Kahneman calls system 2 thinking can reduce cognitive foibles, including reducing the harmful effects of partisan bias. Bago et al. [2020] examines the role of deliberation in reducing false beliefs from false and true news headlines. The idea is the intuition is likely more biased than deliberative thinking. In their experiment, respondents were asked for an initial, intuitive response under time pressure and concurrent working memory load. They were then given an opportunity to rethink their response with no constraints, thereby permitting (but not requiring) more deliberation. They found that deliberation corrected intuitive mistakes: Participants believed false headlines (but not true headlines) more in initial responses than in final responses. This suggests that professional forecasts could reduce or even eliminate partisan bias by using their professional expertise and rigorous modeling.

It also suggests that professional forecasters, trained in formal deliberation, should be less biased than lay people are in forecasts like the Michigan-survey. Gillitzer et al. [2021] find that in United States and Australia, consumers expect significantly lower inflation when the political party they support holds executive office. This finding cannot be explained by previously documented sources of heterogeneity in consumer inflation expectations. Some economics forecasts, particularly the anonymous ones and among the public, may simply be cheap talk with low effort. Kempf et al. [2021] look at a situation with real consequences, capital allocation across countries. They provide evidence from syndicated corporate loans and equity mutual funds that shows ideological alignment with foreign governments affects the cross-border capital allocation by U.S. institutional investors. They also find that ideological distance between countries also explains variation in bilateral investment. Mian et al. [2021] shows that the rise in U.S. political polarization over the past 20 years was a substantial increase in the effect of partisan bias on survey-based measures of economic expectations. Individuals have a more optimistic view on future economic conditions when they are more closely affiliated with the party that controls the White House, a force that has increased significantly over time. Administrative data on spending shows no effect of these shifts on actual household spending.

But not all professionals avoid these cognitive pitfalls. Arikan et al. [2022] looks at partisan affiliations among US CEOs and finds that when they share a party with the US president they are more likely to issue optimistic economic forecasts and disclosures, and more likely to use less conservative accounting choices. This is somewhat similar in spirit to our paper, because CEOs, like the WSJ economist forecasters, are trained professionals with an economic incentive to rationally forecast economic conditions. Arikan et al. [2022] finds that, like we do in the economists, that their training and expectations are insufficient to fully overcome the consequences of partisan affiliation.

3 Data

3.1 The WSJ Economic Forecasting Survey

The WSJ has been periodically surveying professional economic forecasters since the mid-1980s (DeBarros [2022]).[3] The WSJ survey has changed several times since the 1980's, resulting in a variety of questions, frequencies, and forecast horizons.[4] The survey is conducted mostly as source material for WSJ news articles rather than academic research. These changes meet the evolving needs of the newsroom such as addressing the topics of the day. Nevertheless, they consistently ask questions about economic growth, employment, inflation, and interest rates.

Unusually among economic forecasts (or surveys of any sort really), the WSJ survey respondents are identified by name (*eponymous*, in contrast with other typically *anonymous* surveys). This allows us to join individual forecasts to individual specific controls and treatments. This feature was first explored by Cho and Hersch [1998] to look at work and education shape forecast accuracy. Our contribution is to link forecasts to measures of individual partisanship of the forecaster. To measure partisanship, we use multiple publicly available and commercial data sources:

The WSJ survey is published as a series of spreadsheets, one survey per spreadsheet.[5]. We standardize the organization of the data and definitions to the extent possible across surveys, and then combine into an unbalanced panel. In some cases (about 10% of raw survey responses), several economists jointly submit a response to the WSJ survey. In these cases we split the multi-person submissions into duplicated individual responses.[6]

3.2 Partisanship Data Sources

To identify political partisanship, we use several sources. First, we look for partisan political donations by the participating economists in the Federal Election Commission (FEC) database.[7] To appear in these data a donor must give $200 or more to a single candidate for federal office in a year.[8] This is

[3] According to McNees [1992], the survey was conducted by financial journalist Tom Herman in its early days.

[4] Interest rate forecasts for the next six months have been collected since 1982, and for the next year since 1984; forecasts of real GNP, the CPI, and the unemployment rate have been collected since 1986. As of April 2021, the WSJ conducted their survey quarterly—in January, April, July, and October—although they sometimes conduct news inspired brief surveys in between. From the mid-1980s through 2002, the WSJ conducted the survey twice a year. From 2003 through March 2021, its frequency was monthly.

[5] DeBarros [2022] provides links to each survey file from 2003 to 2022. As discussed above, the survey data go back to the 1980's, but these forecasts are not posted publicly. We use only the publicly available data.

[6] For example, Saul Hymans, Joan Crary, and Janet Wolfe submitted a common forecast to the February 2007 WSJ survey. We treat this as three separate submissions for the purposes of our analysis.

[7] These data are public and we access them through the FEC's Individual Contributions website.

[8] In general, federally registered political committees and campaigns report political donations of $200 with the name, employer, date, recipient, and other contributor details. In some cases, smaller contributions are also reported. We use all contributions as reported.

a strong indication of partisanship because such donations are rare among American adults. Evers-Hillstrom et al. [2020] estimate that just 0.51 percent of the United State population contributed enough to appear in the FEC data. In contrast, 66.8 percent of voting age Americans voted in the 2020 presidential elections (131x more common).[9] For each economist we can identify in the FEC data, we aggregate the dollars donated to candidates by political party. We call anyone who donates 90%+ of their total observable donations (before, after, or during the forecasts) to one party as having a partisan affiliation with that party and otherwise code the donations as uninformative.[10] We classify the political affiliations of NUMBER surveyed economists by this method.

Partisan employment is another rare political activity that gives a strong signal on personal partisan affiliation. Therefore, we next search public internet sources (personal websites, Wikipedia, speaker biographies for events, posted CVs, social media, and other sites) for the employment history of the surveyed economists to identify partisan employment. Specifically, we look for direct employment for federal elected official (such as a policy advisor for a senator), elected office (e.g., mayor), employment for a partisan committee or organization (e.g., a congressional committee), or an appointed or obviously political position in the executive branch (e.g., comptroller of the currency). For example, Richard Berner was appointed by President Obama as director of the Office of Financial Research (OFR) and served from 2013 until 2017. As with the FEC reported political campaign contributions, such partisan employment can be before, after, or during the forecasts. We classify the political affiliations of NUMBER surveyed economists by this method. Our research showed no cases where an economist had partisan employment for more than one party.

Finally, if we cannot identify partisan affiliation through donations or employment, we identify partisanship through their party affiliation as indicated by voter registration. The purported purpose of such affiliation is to participate in choosing candidates in primary elections, but some voters may choose their affiliation for expressive reasons. McGhee and Krimm [2009] observes that such expressive affiliation is an important channel because voters can safely register with a third party or as an independent (as no party) without giving up their right to choose a major-party candidate in the general election.

Admittedly, this is a weaker measure of partisanship. Registration is free and may simply represent cheap talk. Voters may split tickets in general elections even if registered with a given party. In some areas, one party routinely receives a super-majority of the votes. In such places, the general election is usually a formality, and the key election is the majority party primary, inducing some voters to strategically change their partisan affiliation. Nevertheless, it is plausible and indeed likely that party registered voters are more strongly partisanly affiliated with those parties than independents and the

[9] Census report on turnout in 2020.

[10] In most cases (82%), FEC recorded donations of the surveyed economists are exclusively to one party.

unregistered. We prefer the prior two methods of determining partisan affiliation, but we use this to get the largest sample possible. Our voter registration data are from Civitech, where one of the authors works, based on licensed voter registration data.[11] Unfortunately, voter registration is not available in all states and not widely or reliably available before 2008. Rather than make use of the very limited available within person registration variation, we use the latest available registration for each economist we can match to a registration.

3.3 Measures of political control

We use two main approaches to measure the degree of political control. First, we use the party of the President as a simple measure of political control. This is a strategy widely employed in the literature, see for example: Alesina [1988], Blinder and Watson [2016], Gillitzer et al. [2021], Mian et al. [2021]. In our sample, we have roughly equal number of years between Democratic and Republican presidents: 8 years of Democratic control (all under Barack Obama) and slightly more than 8 years of Republican control (4 under Donald Trump and a little over 4 under George W. Bush).

Second, we use a more granular measure of political control: David Roper's Democrat Control Index [Roper, 2002].The Democratic Control Index is defined as shown in Table 1. To confirm the specific party control of US government, we use the U.S. House website page on party government [Office of the House Historian, 2023].

Table 1: A diagram showing the Democratic Party Control Index

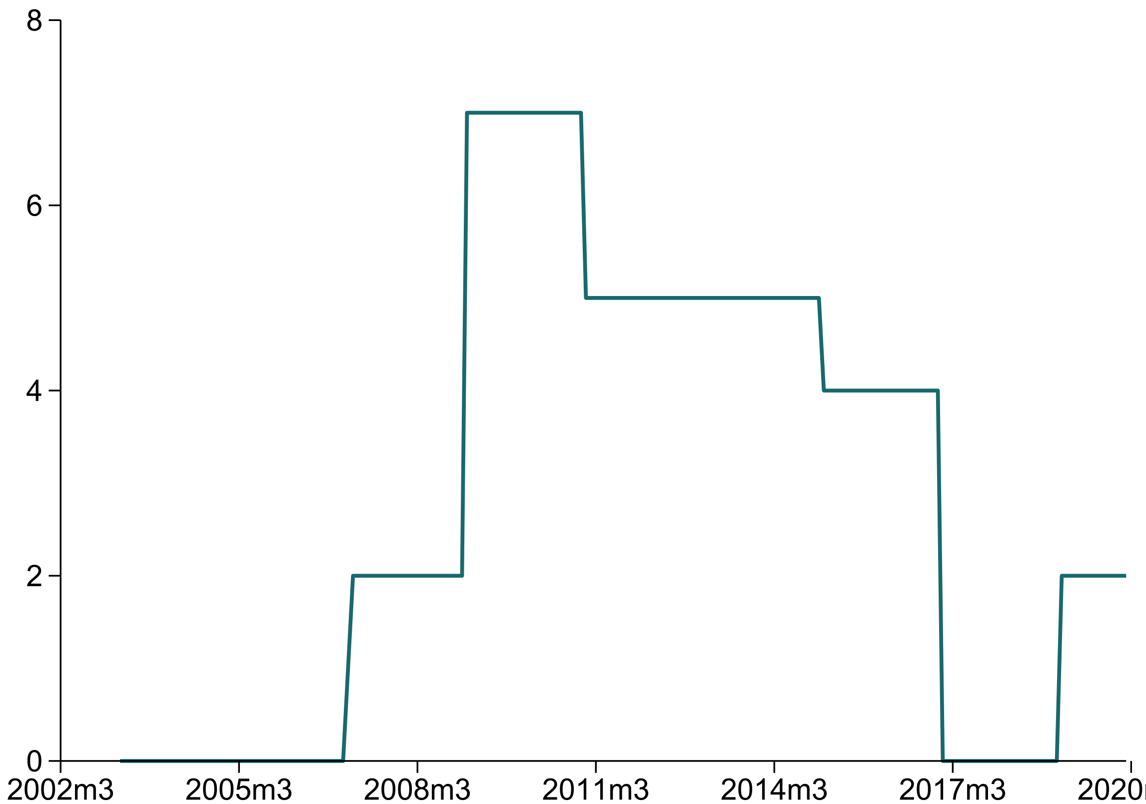
Democratic Control	**Democratic Party Control Index**	**Republican Control**
Nothing	0	President, House, and Senate
Senate	1	President and House
House	2	President and Senate
House and Senate	3	President
President	4	House and Senate
President and Senate	5	House
President and House	6	Senate
President, House, and Senate	7	Nothing

Source: Roper [2002]

Figure 2 shows that the measure varies over the full range of values (from 0 to 7) over our sample. In the second term of the George W. Bush administration, Republicans have control of all three branches and the Roper measure is 0. With the election of Barack Obama, Democrats gain complete control with a corresponding index of 7. Then, with the Trump election, Republicans take back complete control in 2017. This means that we have substantial variation in the political control measure in our sample to identify the differential impact of political control on Republicans and Democrats.

[11] In a few cases where Civitech data was not available or did not uniquely identify a suitable registered voter based on our information, we were able to identify party registration with the Lexis-Nexis public records data.

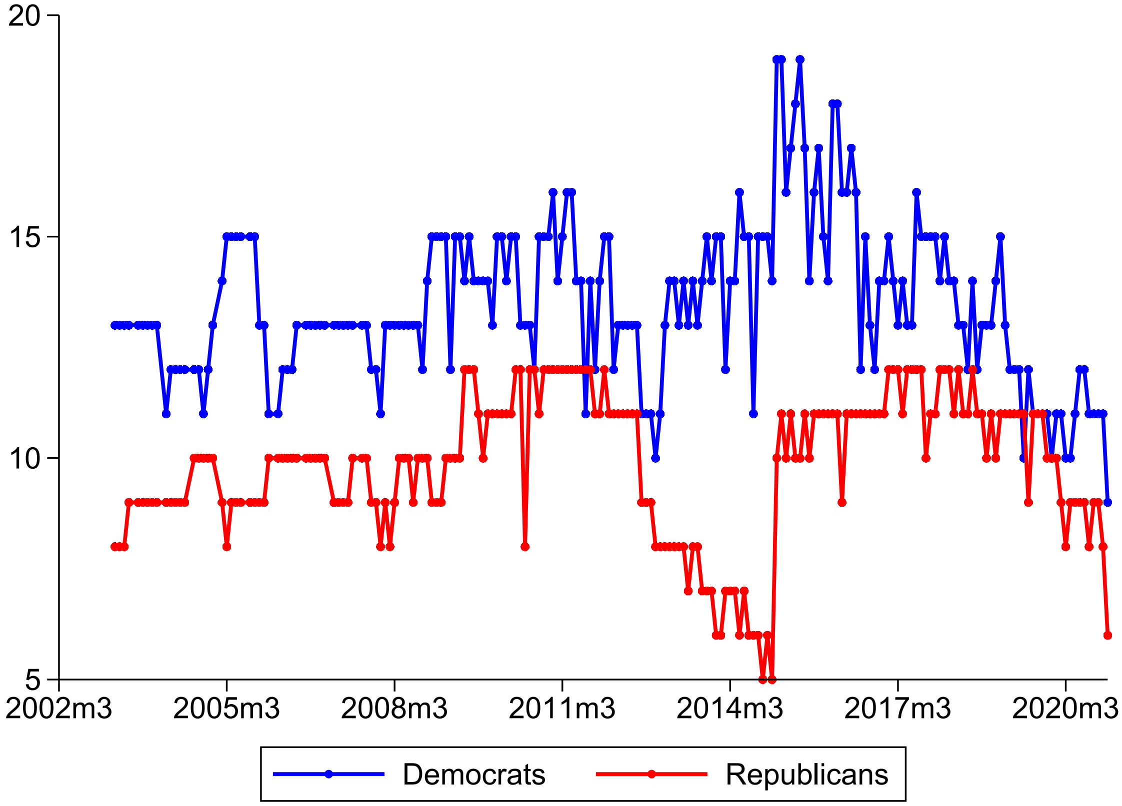
Figure 2: Roper measure of political control



The figure shows the Roper measure of political control. A value of 0 represents complete Republican control of the House, Senate and presidency while a value of 7 represents complete Democratic control. See Section 3.3 for details.

Source: Office of the House Historian [2023] and Roper [2002].

Figure 3: Number of forecasters by political affiliation



This figure shows how many forecasters we are able to match with their political affiliation in each month of our sample. Source: The Wall Street Journal, FEC, Civtech, and author's calculations.

4 Results

Our sample runs from June 2003 to January 2020. In this sample, we are able to successfully categorize 35 forecasters as having a Democratic affiliation and 27 as having a Republican one. Figure 3 shows how many matched forecasters we have by affiliation for each month in our sample.

We have more Democratic aligned forecasters in any given month, which is consistent with earlier research showing that both academic economists (Langbert et al. [2016]) and federal reserve economists (Kuvvet [2022]) are more likely to be affiliated with the Democrats than with the Republicans. We actually find a much larger Republican share for economists than in those papers, which is likely because, as noted in Cho and Hersch [1998], the economists in our WSJ sample are mostly employed by investment or commercial banks. Figure 3 shows the total number of matched forecasters varies over our sample. We have at least 8 matched Democrats and 5 matched Republicans in each month.

Table 2 shows some summary statistics for the macroeconomic forecasts based on constant horizon measures that we created from the WSJ forecasts. In our sample, the WSJ forecast questions change frequently and typically ask for macro forecasts at the end of the current year, next year, and so on.

Table 2: Summary statistics for macro forecasts

Variable	Obs	Mean	Std. Dev	Min	Max
CPI 1Q	2,160	1.948	1.124	-3.6	6.6
CPI 2Q	2,381	2.059	0.839	-3.3	5
CPI 3Q	2,159	2.026	0.679	-2.7	4.8
CPI 4Q	1,755	2.073	0.601	-2.7	5.7
U 1Q	2,166	6.134	2.005	1.5	10.5
U 2Q	2,376	6.014	1.948	1.7	10.8
U 3Q	2,188	5.987	1.965	1.9	10.6
U 4Q	1,800	5.857	1.916	2.7	10.8
GDP 1Q	4,380	2.526	1.244	-6	6.8
GDP 2Q	4,352	2.653	0.986	-3.3	7.8
GDP 3Q	3,661	2.719	0.861	-2.6	7.3
GDP 4Q	1,912	2.773	0.800	-2.3	6

This table shows the summary statistics for GDP, unemployment and CPI inflation forecasts for horizons of 1, 2, 3, and 4 quarters ahead. The sample runs from June 2003 to February 2020. Source: The Wall Street Journal and author's calculations.

However, for econometric analysis, we need constant-horizon forecasts (e.g., forecasts of unemployment 1 quarter ahead). As visible in the Table 2, transforming the data into constant-horizon forecasts causes the data to have different numbers of observations at different horizons. For the baseline results we focus on 2 quarter ahead GDP forecasts.

In the introduction, we highlighted our main results by focusing on raw GDP forecast data together with a simple mean calculated for Democratic and Republican affiliated forecasters. To test how political affiliation of forecasters affects their macroeconomic forecasts more formally, we run a simple regression to compute the statistical significance of the difference in mean forecasts. Specifically, we want to compare how forecasts differ between Democrats and Republicans based on the political regime. We first use the president's party to indicate political control.

Denote the macro forecast for forecaster j as $y_{j,t}$. $Dem_j = 1$ if forecaster j has a Democratic affiliation (and zero otherwise). The indicator variable $Pres_t = 1$ if the president is Democratic (again, zero otherwise). We run the following regression on only the matched sample of 62 forecasters.

$$y_{j,t} = \beta_0 + \beta_1 Dem_j + \beta_2 Pres_t + \beta_3 Dem_j * Pres_t + \varepsilon_{j,t} \tag{1}$$

From these estimated coefficients, we create a 2 x 2 table of the four combinations of Democrat-Democrat, Democrat-Republican, Republican-Democrat and Republican-Republican where the 1^{st} part corresponds to political affiliation of the party and the 2^{nd} part corresponds to the party of the president. For example, the Democrat-Republican entry represents the average Democratic forecast in years with a Republican president with the mean equal to$\alpha + \beta_1$ and so on. We focus on 2-quarter ahead GDP forecasts (in Table 3). However, the results for all the other horizon GDP forecasts are similar. We compute standard errors by clustering at the forecaster level.[12]

Democratic forecasters are more optimistic about GDP growth when there is a Democrat in the White House. Specifically, their average GDP forecast is 2.64% under Democratic presidents but 2.49% under Republican presidents. This difference of 0.15 percentage points between the two is shown in the last row. Republicans on the other hand are more optimistic when there is a Republican in the White House. Their average GDP forecast is 0.26% higher with a Republican president. The difference in the last column show how Democrats' average forecast compares to Republicans under the two different parties in the White House. Interestingly, we observe that under Democratic presidents, there is no difference between average Democratic or Republican forecasts. However, under Republican presidents there is a huge difference of 0.4 percentage points. Our main point of interest is to see how the difference-in-differences estimate, i.e., the difference between Democratic and Republican forecasts under Democratic and Republican presidents. This number is reported in the bottom right. The magnitude is substantial at 0.4 percentage points and is strongly statistically significant with a p-value = 0.01.

Table 3: GDP forecasts by forecaster affiliation and president's party

		Forecaster Affiliation			
		Democrat	Republican		Difference
President's party	Democrat	2.64	2.64		0.00
	Republican	2.49	2.90		-0.41
	Difference	0.15	-0.26	Diff-in-diff	0.41
				p-value	0.01

These are the mean forecasts for two-quarter ahead GDP forecasts constructed from estimated coefficients in Equation 1. The sample is June-2003 to February 2020. p-value is computed with standard errors clustered at the forecaster level. Source: The Wall Street Journal, FEC, Civtech, and author's calculations.

The differences-in-differences estimation of Equation 1 averages across forecasters and thus our identification is potentially coming from a combination of within-forecaster and between-forecaster variation over time. Next, we estimate a more "stringent" specification where we include both forecaster (γ_j) and time (γ_t) fixed effects. This will force the identification to come from variation within forecasters over time. This specification is the canonical two-way fixed effects estimator given by

$$y_{j,t} = \gamma_j + \gamma_t + \beta Dem_j * Pres_t + \varepsilon_{j,t} \tag{2}$$

[12] Bertrand et al. [2004] concludes that more than 30 clusters are usually needed for asymptotic results on standard errors to apply. Using improved bootstrap based methods, Cameron et al. [2008] estimates that the empirical test rejection rates are extremely close to the theoretical values with as few as six clusters. We use a classical cluster-robust estimator which performs well when the number of clusters is as large as ours is.

Table 4: Difference in Democratic and Republican GDP forecasts by party of president

Dem_j x $Pres_t$	0.36***
	(0.093)
Observations	4,352
R-squared	0.624

This table shows the two-way fixed effects estimate of the differential response of Democratic and Republican forecasters with Democratic presidents relative to Republican presidents, i.e. coefficient β from Equation 2 for two-quarter ahead GDP forecasts. The sample is June-2003 to February 2020. Standard errors reported in parentheses are clustered at the forecaster level, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ Source: The Wall Street Journal, FEC, Civtech, and author's calculations.

Table 4 shows the two-way fixed effects coefficient β from Equation 2.[13] Even with the forecaster and time-fixed effects, the size of the coefficient (0.36) is very close to the estimate of $\beta_3 = 0.41$ from Equation 1. Moreover, this effect is strongly statistically significant with a p-value < 0.01.

Having shown the partisan forecasting bias exists across presidential regimes, we now investigate the more granular Roper measure of political control and its relationship with macroeconomic forecasts. As shown in Figure 2 this measure varies from 0 representing full Republican control to 7 representing full Democratic control. In our sample there are no observations where the Roper measure takes on a value of 2 or 6.

Table 5: Difference in Democratic and Republican GDP forecasts by Roper measure

Dem_j x Roper = 2	-0.28***
	(0.092)
Dem_j x Roper = 4	0.02
	(0.094)
Dem_j x Roper = 5	0.26**
	(0.129)
Dem_j x Roper = 7	0.46***
	(0.173)
Observations	4,352
R-squared	0.629

These are the mean the two-way fixed effects estimate of the differential response of Democratic and Republican forecasters by Roper index i.e. coefficients β^j from Equation 3 for two-quarter ahead GDP forecasts. The sample is June-2003 to February 2020. Standard errors reported in parentheses are clustered at the forecaster level, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ Source: The Wall Street Journal, FEC, Civtech, and author's calculations.

As above, we follow the same two-way fixed effects approach to measure how forecasts differ con-

[13] There has been a growing recent literature pointing out issues with estimating these two-way fixed effects (Goodman-Bacon [2021], De Chaisemartin and d'Haultfoeuille [2020]). But in our case, the "treatment" (i.e., change in political control) is not staggered. It applies to all the forecasters at the same time and therefore these recent concerns do not apply.

ditional on various values of the Roper political control measure. We create indicator variables for the Roper index by Rop_t. Then we estimate the following equation.

$$y_{j,t} = \gamma_j + \gamma_t + \sum_{i \in \{2,4,5,7\}} \beta^i Dem_j * Rop_t^i + \varepsilon_{j,t} \tag{3}$$

Table 5 presents the interaction coefficients (β^i) from the above equation. The Roper index = 0 is the base category for the regression. Thus the interaction coefficients give us the difference-in-difference estimates, viz. difference between Democrat and Republican-affiliated forecasters when the Roper index is j (with $j \in \{2, 4, 5, 7\}$ relative to when the Roper index is 0 (which represents complete control by Republicans).

Table 5 reports standard errors clustered at the forecaster level. Relative to the Democrat-Republican difference when Roper index is 0, higher levels of Roper index (4, 5, or 7) are related to Democrats having higher GDP forecasts relative to Republicans. For example, when the Roper index is 7, Democrat affiliated economists in the WSJ survey have a GDP forecast that is 0.46 percentage points higher than Republicans affiliated economists, relative to a Roper index = 0. This is consistent with our earlier results using the President's party as the measure of political control.

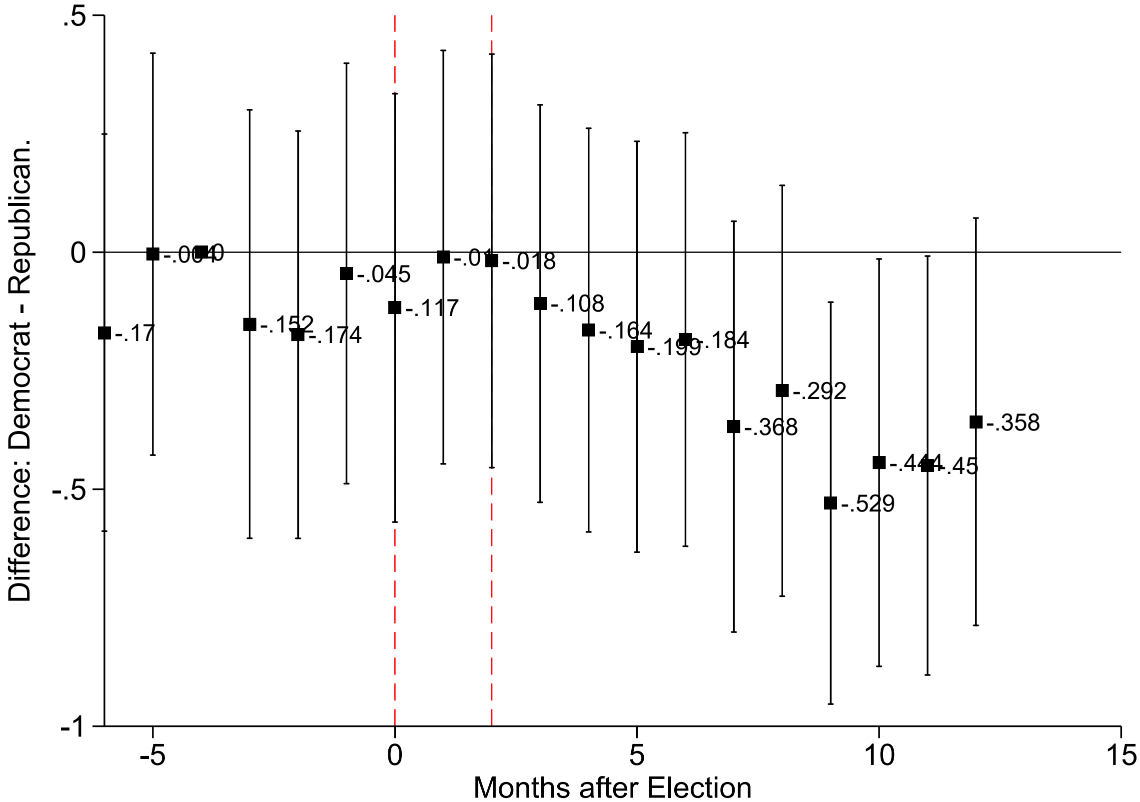
Figure 2 shows that there are two changes in president. Not surprisingly, these two instances are also when the Roper measure changes substantially. First, with the election of Barack Obama, the Democrats take control of the Senate, House, and the presidency in January 2009 and the Roper measure goes from 2 to 7. Second, with the election of Donald Trump, the Republicans now take control of all three in January 2017 and Roper measure goes from 4 to 0. In addition, we have instances when only control of the Senate or House changes the Roper measure. For example, taking it from 0 to 2 in 2006 mid-term election or from 5 to 4 in the 2014 midterm elections.

The results in Table 5 show that there is statistically significant difference in the effect for Roper measure being equal to 2, 5 and 7 but not 4. We conservatively interpret this is as evidence that changes in the composition of the Senate and the House also appear to be systematically related to the partisan tilt in the macroeconomic forecasts.

To provide more context for the importance of presidential elections for our results, we estimate event-study regressions around these two election dates. Specifically, we estimate Equation 1 only using a 18 month window around the election. Specifically, this sample includes forecasts from 6 months before the election to establish a "pre-trend" and then shows the differential impact of the election on Democratic and Republican affiliated forecasters for 12 months after the elections.

Figure 4 shows the results for the 2016 election. The two red lines show the election dates of November 2016 and the inauguration date of Donald Trump of January 2017. As discussed above, the difference between Democratic and Republican forecast for GDP growth is very similar over the

Figure 4: Difference in Democratic and Republican GDP forecasts around 2016 Election

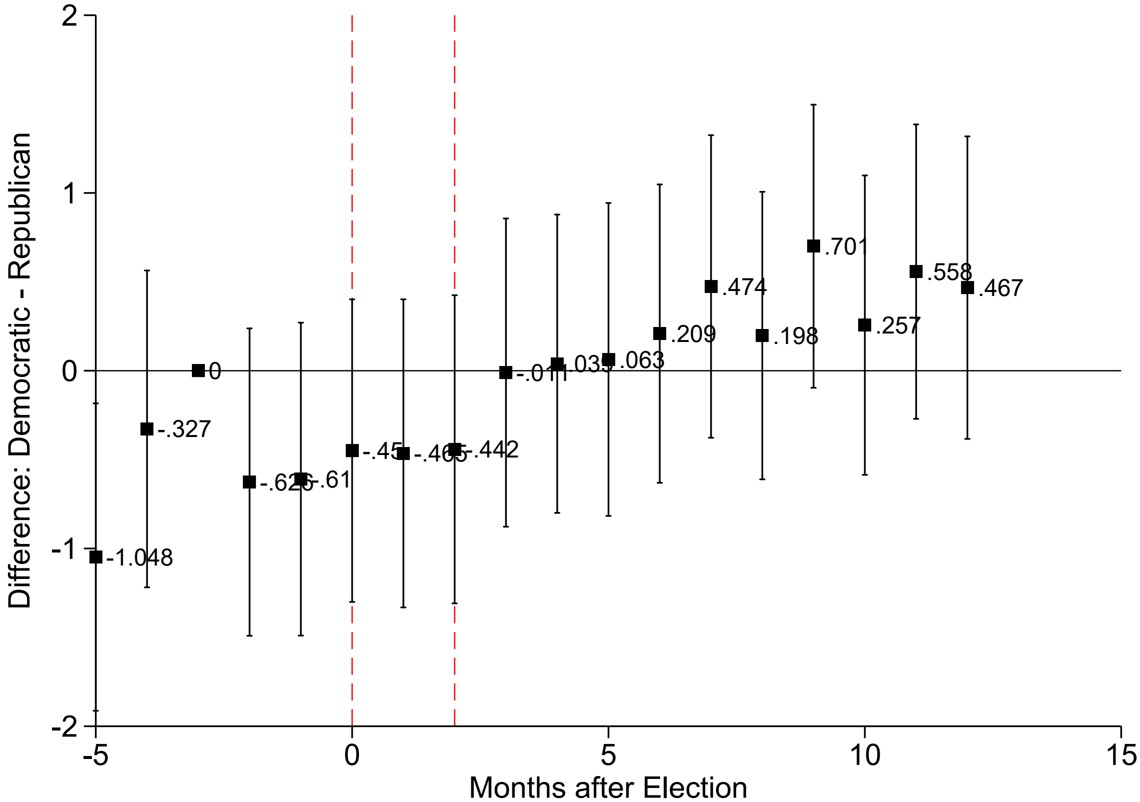


This figure shows the estimate of the differential response of Democratic and Republican forecasters with Democratic presidents relative to Republican presidents, i.e. coefficient β from Equation 1 for two-quarter ahead GDP forecasts. The sample is May-2016 to October 2017. 95% confidence intervals based on standard are reported. Source: The Wall Street Journal, FEC, Civtech, and author's calculations. Source: The Wall Street Journal, FEC, Civtech, and author's calculations.

Obama presidency. Consistent with this, in the six months leading up to the 2016 election, there is no statistically significant difference between Democrats and Republicans. The figure also shows that, in the months after the inauguration of President Trump, there appears a growing difference between Democratic and Republican forecasters. The peak difference occurs nine months after the election with an effect that is statistically different from zero at the 5% level. The size of the effect is substantial: nine months after the election Democratic forecasts for GDP growth are 0.5 percentage points lower than Republicans relative to before the election.

Figure 5 shows the event-study results for the 2008 election. Again, the two red lines demarcate the election and the inauguration dates. Under the second term of President Bush, the average Democratic GDP forecast is lower than the average Republican forecast. This can be seen with the negative coefficients in the figure before the election date. Like the Trump election, after the Obama election

Figure 5: Difference in Democratic and Republican GDP forecasts around 2008 Election



This figure shows the estimate of the differential response of Democratic and Republican forecasters with Democratic presidents relative to Republican presidents, i.e. coefficient β from Equation 1 for two-quarter ahead GDP forecasts. The sample is May-2008 to October 2009. 95% confidence intervals based on standard are reported. Source: The Wall Street Journal, FEC, Civtech, and author's calculations.

the affiliation of the forecasters with the President's party has a sizeable effect on GDP forecasts. In this case, Democratic forecasts become more optimistic relative to Republican forecasts, although the estimation is noisier, and the results are marginally significant (10% level). The peak effect is again at the nine-month mark after the election suggesting that 9 months after the election Democratic GDP forecasts are 0.7 percentage points higher than Republican forecasts relative to before the election. Overall, these two event studies confirm our full-sample results that when there is a change in the president it has a noticeable effect of making forecasters affiliated with the part of the president becoming relatively more optimistic in their GDP growth forecasts.

5 Conclusion

There is well established evidence that household expectations in the US are strongly driven by political polarization (e.g., Gillitzer et al. [2021], Binder [2023]). In this paper, we document that partisan bias even affects the macroeconomic forecasts of professional forecasters. We find that forecasters, affiliated with the political party in control, are more optimistic about economic growth than forecasters affiliated with the opposition party. Specifically, we find that the GDP growth forecasts of Democrat-affiliated forecasters are 0.4 percentage points higher than Republican forecasters when there is a Democratic president. In addition to the importance of the executive branch, we also find suggestive evidence that changes in the control of the House and the Senate affect the forecasters based on their political affiliation.

There is a growing literature that studies, using survey data, how professional forecasters deviate from the full-information rational friction-less benchmark pervasive in macroeconomics. Our results suggest that an additional (and previously unexplored) reason for deviation from this benchmark is related to political affiliation. With overall political polarization increasing in the US in recent decades (Fiorina and Abrams [2008]), exploring this issue in greater detail is a fruitful area for future research.

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